Association for Information Systems
AIS Electronic Library (AISeL)

PACIS 2018 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

6-26-2018

Economics of 'Tipping' Button in Social Media: An Empirical Analysis of Content Monetization

Ruibin Geng
Xidian University, grace.bin1207@gmail.com

Xi Chen
Zhejiang University, chen_xi@zju.edu.cn

Economics of 'Tipping' Button in Social Media: An Empirical Analysis of Content Monetization

Completed Research Paper

Ruibin Geng
Xidian University
No.2 South Tai Bai Rd., Xi'an
rbgeng@xidian.edu.cn

Xi Chen[1]
Zhejiang University
No.388 Yu Hang Tang Rd., Hangzhou
chen_xi@zju.edu.cn

Abstract

As the success of social media platforms heavily depends on the amount and the nature of user-generated content, content monetization has been introduced as a mechanism to incentivize users to generate content. In particular, content contributors can be paid (i.e. tipped) by readers who like the story. We adopted difference-in-differences approach with robustness matching estimator to examine the impact of content monetization. Our results confirm that the content monetization effectively motivate content demand and supply and also improves content quality. Furthermore, such economic incentives have a spillover effect on ordinary weibo users before they are eligible to adopt "tipping" function. However, the verified users who have already been the experts or celebrities in the society may be depressed after open application of the program. This result suggests that start-ups are able to survive and earn profit even in markets that are dominated by famous celebrities because of the monetization mechanism.

Keywords: Content monetization, content supply, content quality, content demand, user-generated content, economic incentives

Introduction

With the maturity of social media, online review systems, and collaborative forum, user-generated-content (UGC) has reached such high levels of quantity and variety that it is comparable to that produced by professional agencies. The greatest value of UGC website from the perspective of users is that these platforms provide huge amount of user-generated content (UGC) that becomes crowdsourced knowledge shared through the networks (Albors et al. 2008). However, UGC platforms hold potential low engagement risks because of two main reasons. On the one hand, consumers are expecting their social media consumption to be free; on the other hand, casual internet users often lack domain expertise and they may lack incentives to contribute in a crowd environment (Lukyanenko et al. 2014). As a result, content providers are under increasing pressure to monetize their content.

Major social media platforms are seeking innovative content monetization strategies to get users to spend money on existing content, in addition to traditional advertisement-sponsored revenue model. An increasingly popular option of content monetization is the donation button (also referred as "tip" button in Sina Weibo or "buy me a coffee" button supported by PayPal), which allows content consumers to donate any amount of money to the original content creators. This process generates local positive feedback between content generation and content consumption, which thereby produces a self-reinforcing "virtuous cycle" and actives the whole platform.

[1] Xi Chen, School of Management, Zhejiang University, Alibaba-Zhejiang University Joint Institute of Frontier Technologies.

The introduction of content monetization mechanism is the latest prevalent practice to incentivize content generation and consumption in UGC market. The extant research on content generation primarily focus on the research questions of how online users are incentivized to generate UGC when lacking direct monetary incentives (Chen et al. 2010, Trusov et al. 2010). These factors include user characteristics (Bateman et al. 2011), characteristics of the social network (Zhang and Zhu 2011), and information system design features (Moon and Sproull 2008). In addition, the impact of UGC on content consumers' activities are investigated independently in another UGC literature branch (Mishne and Glance 2006; Goh et al. 2013). Researchers have attempted to identify the impact of UGC on product sales (Jabr and Zheng 2013), stock performance (Tirunillai and Tellis 2012), and even the success of social media site (Susarla et al. 2012) in online communities. As it is demonstrated above, existing studies tend to focus on one perspective, either from the demand side (Singh et al. 2014; Susarla et al. 2012) or supply side (Goes et al. 2014; Zeng and Wei 2013). Therefore, it becomes imperative for both scholars and practitioners to understand the factors that motivate the supply of high quality UGC.

In this study, we propose the introduction of the online donation feature as an effective tool in social media platform to motivate content suppliers to generate high-quality content, which subsequently attracts more content consumers and ultimately increases user loyalty. The introduction of content monetization is regarded as a natural experiment-like change therefore allows for similar identification approaches in field experiment to examine the impact of such exogenous shock. We employ the difference-in-differences (DID) model (Atanasov and Black 2014) combined with matching estimators (Abadie and Imbens 2006) to investigate the impact of content monetization adoption in social media on the supply and demand of UGC as well as the content quality. Our empirical results show that content monetization mechanism effectively motivate the demand and supply for UGC and also improves content quality. Furthermore, such economic incentives have a spillover effect on ordinary weibo users before they are eligible to adopt "tipping" function. However, the verified users who have already been the experts, celebrities or other public figures in the society may be depressed after open application of the program. This result suggests that small, less popular content creators are able to survive and earn profit even in markets that are dominated by larger firms because of the monetization mechanism.

The reminder of this paper is organized as follows. In section 2, we briefly review the relevant literature and discuss how our work extend the existing research. In section 3, we describes the empirical context for our data. In section 4, we adopt a difference-in-differences model that captures the impact of content monetization mechanism. Section 5 makes a further discussion on the empirical results. Section 6 draws conclusions.

Literature Review

Our paper is closely related to the large body of literature on UGC. UGC takes a variety of formats including product reviews, descriptions of product usage, "homemade advertising", blogs, and other consumer-initiated contributions (Fader and Winer 2012). Existing papers have studied a wide range of topics related to content consumption (e.g. how UGC affects individual consumer behavior) and content generation (e.g. why and how people contribute content).

Content Consumption. Many prior studies have examined how various aspects of UGC such as volume, valence, or variance affect user behaviors (Goes et al. 2014). In the information systems literature, UGC has been found to affect business decision making in many contexts, including business applications (Gangi et al. 2010), e-commerce (Zwass 2010), new product development (Mallapragada et al. 2012), adoption of navigation and mapping systems (Haklay 2010), emergency management (Majchrzak and More 2011), scientific research (Hand 2010), healthcare (Gao et al. 2010), and politics (Wattal et al. 2010). In marketing literature, there is ample empirical evidence suggesting the effectiveness of UGC in affecting consumer buying and consumption behavior. For example, Chevalier and Mayzlin (2006) found that consumer ratings positively affect book sales. A few other studies found that buyers seem to find movies and books that have generated numerous reviews more interesting, which in turn drive greater demand, than those movies and books that have not received as many reviews (Dellarocas et al. 2004, Liu 2006).

Content Generation. The literature on content generation has focused primarily on users' motivations to participate. As it is studied in many online contexts, such as open source software (Lerner and Tirole 2002), online forums (Jeppesen and Frederiksen 2006), and blogs (Faw 2012), peer recognition and online reputation are identified as two most important motivations for users' voluntary contributions to UGC. Moe and Schweidel (2012) found two separate effects that may influence individual's decision on whether to submit a product rating on an e-commerce platform. Customers may prefer to be consistent with previously posted ratings by the majority (i.e. selection effect), or otherwise to stand out from the crowd by revising their evaluations upward or downward based on previously posted ratings of others (i.e. adjustment effect). Scott, Nair and Hofstetter (2013) documented that social ties can also facilitate content generation on a social networking site by controlling group formation endogeneity and other confounding factors. The associations between social ties and content generation are linked to several motivations, including altruistic user intention to sharing information with others and a desire to increase social status within a peer group (referred as audience effect). Shen, Hu and Rees (2015) empirically examined how online reviewers' behaviors are driven by the desire to gain attention and online reputation.

Our analysis of user generated content differs from the previous research in two ways. First, we study how content monetization mechanism affects user content generation behavior as well as content consumption behavior, an important but under-researched topic. Second, we adopt a difference-in differences approach to examine the spillover effect of content monetization across different types of users (verified users versus non-verified users).

Data and Context

We collected our data from one of the largest leading social media platforms in the world, Sina Weibo. Weibo allows users to create and post a feed and attach content. Any user can follow any other users and add comments to a feed while reposting. Like other microblogging services such as Twitter, Weibo is still managing to get people to be actively contributing content rather than watching passively. On August 1st, 2014, the company started offering the online donation feature by attaching a "tipping" button to long articles (i.e., blogs exceeding the 140-characters limit) posted on Weibo. From August 2014 to January 2015, the platform conducted a test-run of the "tipping" function and only verified-users are invited to participate in this content monetization practice. Since the test-run ended on January 2015, Sina have accepted applications for the online donation feature from all users. We randomly sampled 10,151 users from the Weibo platform, encompassing 1,127 users who had ever posted at least one articles before the launch of a tipping button, 835 users who posted their first article during the test period, 1,330 users who posted their first articles during the open application period, and 6,859 users who never posted any articles during our sample period between January 2014 and September 2015. The segments of our sampled users based on adoption time of article posting are illustrated in Figure 1.

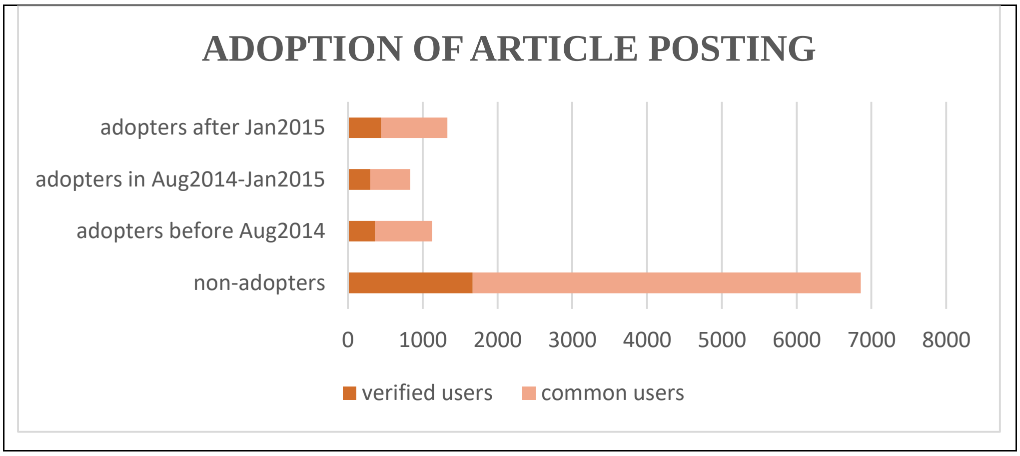

Figure 1. Segments of users based on adoption time of article posting

Our work leverages three types of data, namely, user demographic profile, user content generation data, and content profile information (including article-related and microblog-related features). User demographic profile includes gender, registration time, level, verification type (verified celebrities or not), number of friends, number of followers, number of posts (also called microblogs), which serve as control variables in our model. User content generation data captures users' article posting behaviors from January 2014 to September 2015 together with their microblog posting behaviors from May 2014 to May 2015. The count of articles and microblogs created by users are used as outcome variables of interest to examine the supply of UGC. Article-related profile information contains number of characters, number of pictures, the number of reading, favorite, and tipping obtained by each article, which are also used as outcome variables to measure the article quality and article demand. Microblog-related profile information contains number of microblogs, average number of reposts, comments, favorites obtained by microblogs, which are used as outcome variables to measure microblog supply and microblog demand. Microblogs is regarded as the complementary product for long articles, whose supply is also assumed to be affected by "tipping" incentives.

Based on the article posting data, we focus our analysis on the 3,292 active article authors who have posted at least one article during the observation time, so that it is meaningful to estimate the impact of "tipping" function on the shifts in supply, demand, and quality of articles. In addition to the policy changes at different time periods, we are also interested in the different reactions of verified users and non-verified users to the policy changes. Because during the test period from August 2014 to January 2015, tipping function is only eligible for verified users who posted long articles. However, this policy changed that all long articles posted after January 2015 would automatically have the tipping button, which means that verified users no longer have the privilege to monetize the content. The motivations of verified and non-verified users to post long articles may be affected by those policy changes. Thus, we use verified type of users as one treatment variable and also control the breakpoints of the policy changes as well as the "tipping" enrollment date of each user. Figure 2 demonstrates the trend of article posting across the observed 21 months. Figure 3 shows the number of active users who posted at least one articles in each month. During the test period, only 543 verified users who posted long articles with tipping function. After the announcement of open application, 1586 common users and 972 verified users participate in posting articles with "tipping" button. Table 1 summarizes the descriptive statistics of the variables used for article posting analysis.

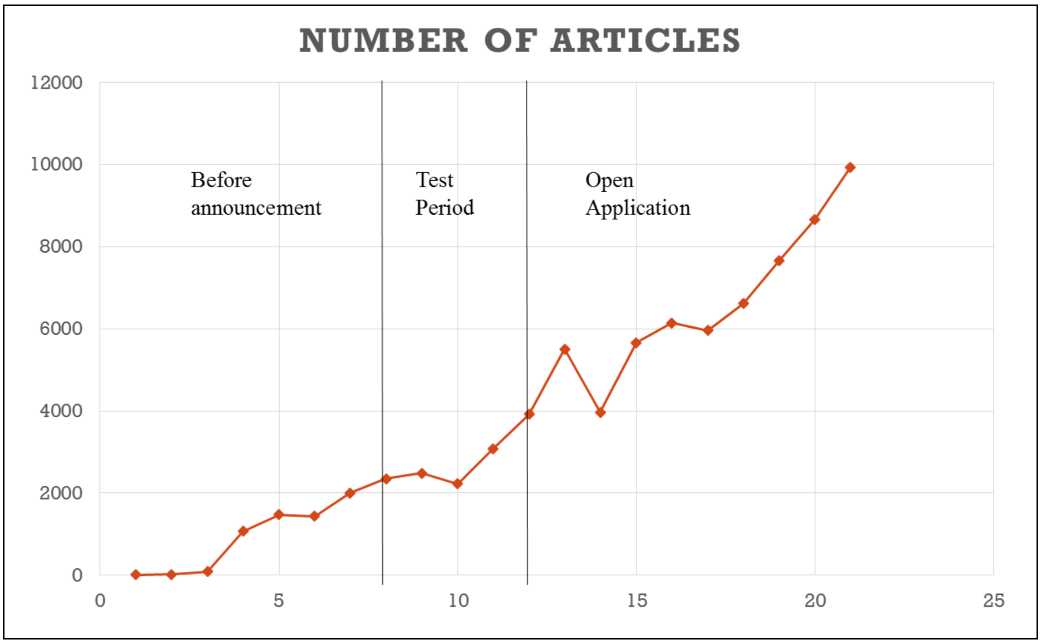

Figure 2. Number of articles created in each month from Jan 2014 to Sep 2015

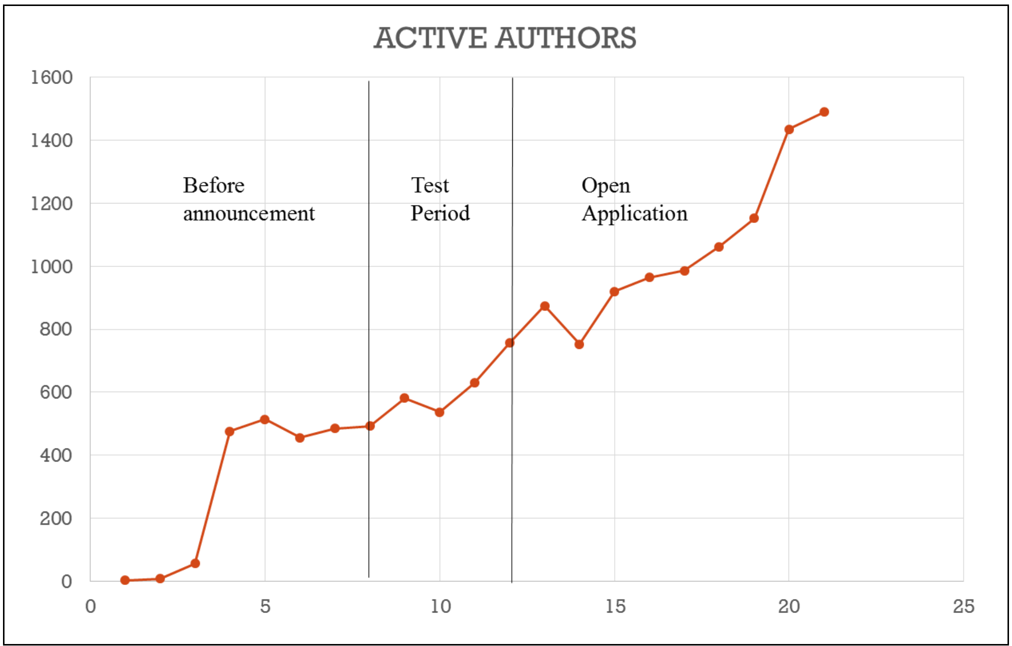

Figure 3. Active authors of long articles in each month during Jan 2014 to Sep 2015

Table 1. Summary statistics of outcome, treatment, and control variables (article posting data)

Article Posting Data			Users:3292	Time:21
Variable	Mean	Std. Dev.	Min	Max
Outcome Variables				
Num_articles	0.926	5.331	0	284
Num_chars	259.998	962.469	0	32759
Num_pics	0.818	5.052		519
Num_reading	1411.287	3266.14	0	4000000
Num_favorite	15.776	764.448	0	180356
Num_tipping	0.95	9.21	0	398
Treatment Variables				
Verifiedtype	0.337	0.473	0	1
$AfterEnroll_{(it)}$	0.319	0.466	0	1
$AfterAug_{(t)}$	0.658	0.474	0	1
$AfterJan_{(t)}$	0.404	0.491	0	1
Control Variables				
Friend_count	590.018	653.812	0	4984
Follow_count	70758.5	456332.2		1.16E+07
Statues_count	5444.361	9167.753	0	113536
Gender	0.542	0.489	0	1
Level	14.867	8.063	0	36
Isvip	0.334	0.472	0	1
Regist_time	1762.48	1665.568	242	42277

Based on the microblogging posting data, we focus our analysis on all the users in our sample including both adopters and non-adopters of tipping button. We aim to examine whether the adoption of the tipping button feature may exert significant influence on users' microblog posting behavior as well. Therefore, "tipping" function adopters and non-adopters are regarded as treatment and control groups respectively. The change of microblog posting behaviors before and after enrollment dates as well as two breakpoints of policy changes (August 2014 and January 2015) are compared between the adopters and non-adopters. Table 2 summarizes the descriptive statistics of the variables used for microblog posting analysis.

Table 2. Summary statistics of outcome, treatment variables, and control variables (microblog posting data)

Microblog Posting Data			Users:6311	Time:12
Variable	Mean	Std. Dev.	Min	Max
Outcome Variables				
Num_microblogs	10.403	52.037	0	4158
Num_comments	243.67	18259	0	3694005
Num_reposts	972.87	163578.4	0	4.43E+07
Num_favorite_micro	678.104	46892.58	0	5429643
Treatment Variables				
Adoption	0.367	0.482	0	1
$\text{AfterEnroll}_{(it)}$	0.128	0.334	0	1
$\text{AfterAug}_{(t)}$	0.248	0.432	0	1
$\text{AfterJan}_{(t)}$	0.157	0.364	0	1
Control Variables				
Friend_count	446.734	544.026	0	4995
Follow_count	50761.07	492562.3	0	1.20E+07
Statues_count	3414.244	6950.351	0	132300
Gender	0.472	0.499	0	1
Level	12.632	7.334	0	37
Isvip	0.212	0.409	0	1
Verifiedtype	0.218	0.413	0	1
Regist_time(day)	1671.277	1433.64	242	42277

Model and Results

We employ a difference-in-differences (DID) model (Atanasov and Black 2014) to evaluate the impact of the online donation feature on the shifts in content supply, content quality, and content demand. Our main estimation equation for user *i* in month *t* is

$$Outcome_{it} = \beta_0 + \beta_1 Treatment_i + \beta_2 After_{it} + \beta_3 Treatment_i \times After_{it} + \beta_3 X_{it} + \tau_t + \varepsilon_{it} \quad (1)$$

where $Outcome_{it}$ is the log-transformed measure of content supply (number of articles or microblogs created by user *i* in month *t*), content quality (the average number of characters, the average number of pictures in articles), or content demand (the average number of readings obtained by articles). $Treatment_i$ is the indicator for users in treatment group. Specifically, in article posting behavior analysis it is denoted as 1 if user *i* is verified as celebrities by Weibo, and 0 otherwise (*i.e.* variable "Verified"), while in microblog posting behavior analysis it is denoted as 1 if user *i* participates in the monetization program, and 0 otherwise (*i.e.* variable "Adopt"). Another binary variable $After_{it}$ is 1 if user i has already adopted the tipping function in month *t*, and 0 otherwise (*i.e.* variable "AfterEnroll").

Considering the policy change between the test period and open application, we redefine $After_{it}$ to indicate whether month *t* is before or after August 2014 and January 2015 (*i.e.* variable "AfterAug" and "AfterJan"). The coefficient β_3 for the interaction term, $Treatment_i \times After_{it}$, is our difference-in-differences estimator that captures how outcome variables change in the treatment group after monetization program enrollment (or after monetization policy changes) in contrast to that of control group in the same period. The individual-specific attributes, such as, number of friends, number of followers, number of statues, gender, level, and registration time are used as control variables in X_{it}. Time fixed effect τ_t is added to control for changes in all bloggers' propensity to produce content across the 21 month. Tables 3 – 7 illustrate the estimation results.

Table 3. Estimation results for shift in article supply (num_article)

Enrollment as Breakpoints		August 2014 as Breakpoints		January 2015 as Breakpoints	
	Coef.		Coef.		Coef.
Verified	-0.239** (0.055)	Verified	-0.413** (0.077)	Verified	-0.007 (0.060)
AfterEnroll	0.679** (0.063)	AfterAug	0.506* (0.051)	AfterJan	0.667** (0.146)
Verified*After Enroll	2.963** (0.087)	Verified*After Aug	1.803** (0.089)	Verified*After Jan	1.855** (0.084)
Friend_count	3.32E-05 (3.44E-05)	Friend_count	2.97E-05 (3.49E-05)	Friend_count	6.38E-05 (3.48E-05)
Follow_count	-7.28E-08* (4.41E-08)	Follow_count	-1.06E-07** (4.47E-08)	Follow_count	-7.83E-08 (4.46E-08)
Statues_count	2.5E-05** (2.41E-06)	Statues_count	2.75E-05** (2.44E-06)	Statues_count	2.91E-05** (2.43E-06)
Gender	0.396** (0.041)	Gender	0.386** (0.041)	Gender	0.428** (0.041)
Level	0.047** (0.003)	Level	0.053** (0.003)	Level	0.052** (0.003)
Isvip	0.287** (0.047)	Isvip	0.303** (0.048)	Isvip	0.328** (0.048)
Regist_time	-3.19E-05** (1.18E-05)	Regist_time	-2.5E-05** (1.19E-05)	Regist_time	-2.37E-05* (1.19E-05)

Table 4a. Estimation results for shift in article quality (num_chars)

Enrollment as Breakpoints		August 2014 as Breakpoints		January 2015 as Breakpoints	
	Coef.		Coef.		Coef.
Verified	-0.067** (0.011)	Verified	-0.129** (0.015)	Verified	-0.017** (0.012)
AfterEnroll	0.278** (0.013)	AfterAug	0.224* (0.097)	AfterJan	0.223** (0.088)
Verified*After Enroll	0.760** (0.017)	Verified*After Aug	0.492** (0.018)	Verified*After Jan	0.504** (0.017)

Friend_count	4.4E-05** (6.8E-06)	Friend_count	5.31E-05** (7.04E-06)	Friend_count	5.31E-05** (7.03E-06)
Follow_count	2.11E-09 (8.81E-09)	Follow_count	2.98E-10 (9.03E-09)	Follow_count	2.98E-10 (9.02E-09)
Statues_count	2.66E-06** (4.81E-07)	Statues_count	3.97E-06** (4.92E-07)	Statues_count	3.97E-06** (4.91E-07)
Gender	0.070** (0.081)	Gender	0.080** (0.008)	Gender	0.080** (0.008)
Level	0.016** (5.64E-04)	Level	0.018** (5.77E-04)	Level	0.018** (5.77E-04)
Isvip	0.078** (0.009)	Isvip	0.090** (0.010)	Isvip	0.090** (0.010)
Regist_time	-7.83E-07 (0.038)	Regist_time	3.28E-06 (2.41E-06)	Regist_time	3.28E-06 (2.41E-06)

Table 4b. Estimation results for shift in article quality (num_pics)

Enrollment as Breakpoints		August 2014 as Breakpoints		January 2015 as Breakpoints	
	Coef.		Coef.		Coef.
Verified	0.065 (0.053)	Verified	-0.123 (0.073)	Verified	0.030 (0.057)
AfterEnroll	0.230** (0.061)	AfterAug	0.629** (0.240)	AfterJan	0.716** (0.144)
Verified*After Enroll	1.983** (0.084)	Verified*After Aug	1.303** (0.085)	Verified*After Jan	1.670** (0.081)
Friend_count	1.33E-04** (3.32E-05)	Friend_count	1.51E-04** (3.33E-05)	Friend_count	1.51E-04** (3.33E-05)
Follow_count	7.07E-08* (4.25E-08)	Follow_count	6.78E-08 (4.27E-08)	Follow_count	6.78E-08 (4.27E-08)
Statues_count	-3.88E-06* (2.32E-06)	Statues_count	-1.69E-06 (2.33E-06)	Statues_count	-1.69E-06 (2.32E-06)
Gender	-2.52** (0.039)	Gender	-0.235** (0.039)	Gender	-0.235** (0.039)
Level	1.26E-05 (0.003)	Level	0.003 (0.003)	Level	0.003 (0.003)
Isvip	0.522** (0.046)	Isvip	0.547** (0.046)	Isvip	0.547** (0.046)
Regist_time	7.48E-05** (1.14E-05)	Regist_time	7.95E-05** (1.14E-05)	Regist_time	7.95E-05** (1.14E-05)

Table 5. Estimation results for shift in article demand (num_reading)

Enrollment as Breakpoints	August 2014 as Breakpoints	January 2015 as Breakpoints

	Coef.		Coef.		Coef.
Verified	-0.084** (0.009)	Verified	-0.158** (0.012)	Verified	-0.044** (0.010)
AfterEnroll	0.184** (0.010)	AfterAug	0.351** (0.048)	AfterJan	0.261** (0.059)
Verified*After Enroll	0.836** (0.014)	Verified*After Aug	0.546** (0.014)	Verified*After Jan	0.583** (0.014)
Friend_count	6.23E-07 (5.50E-06)	Friend_count	9.15E-06 (5.69E-06)	Friend_count	9.15E-06 (5.67E-06)
Follow_count	9.89E-08** (7.06E-09)	Follow_count	9.74E-08** (7.29E-09)	Follow_count	9.74E-08** (7.27E-09)
Statues_count	2.10E-06** (3.85E-07)	Statues_count	3.24E-06** (3.97E-07)	Statues_count	3.24E-06** (3.96E-07)
Gender	0.031** (0.007)	Gender	0.040** (0.007)	Gender	0.040** (0.007)
Level	0.019** (4.52E-04)	Level	0.021** (4.66E-04)	Level	0.021** (4.65E-04)
Isvip	0.154** (0.008)	Isvip	0.166** (0.008)	Isvip	0.166** (0.008)
Regist_time	6.52E-07 (1.88E-06)	Regist_time	2.94E-06 (1.95E-06)	Regist_time	2.94E-06 (1.94E-06)

Table 6. Estimation results for shift in microblog supply (num_microblogs)

Enrollment as Breakpoints		August 2014 as Breakpoints		January 2015 as Breakpoints	
	Coef.		Coef.		Coef.
Adopt	2.986** (0.470)	Adopt	2.230** (0.6210)	Adopt	3.037** (0.528)
Adopt*After Enroll	6.639** (0.679)	Adopt*After Aug	5.925** (1.041)	Adopt*After Jan	5.110** (0.787)
Friend_count	0.003** (3.97E-04)	Friend_count	0.003** (3.98E-04)	Friend_count	0.003** (3.97E-04)
Follow_count	5.87E-07 (3.90E-07)	Follow_count	5.48E-07 (3.90E-07)	Follow_count	5.53E-07 (3.90E-07)
Statues_count	4.18E-04** (3.17E-05)	Statues_count	4.26E-04** (3.18E-05)	Statues_count	4.20E-04** (3.18E-05)
Gender	4.307** (0.0383)	Gender	-4.388** (0.383)	Gender	4.383** (0.383)
Level	-0.469** (0.032)	Level	-0.452** (0.032)	Level	-0.451** (0.032)
Isvip	-1.231* (0.526)	Isvip	-1.126* (0.526)	Isvip	-1.151* (0.526)
Regist_time	9.39E-05 (1.32E-04)	Regist_time	-7.95E-05 (1.32E-04)	Regist_time	-8.76E-05 (1.32E-04)

Table 7. Estimation results for shift in microblog demand (num_favorite_micro)

Enrollment as Breakpoints		August2014 as Breakpoints		January2015 as Breakpoints	
	Coef.		Coef.		Coef.
Adopt	0.017* (0.006)	Adopt	0.068** (0.012)	Adopt	0.021** (0.006)
Adopt*AfterEnroll	0.190** (0.008)	Adopt*AfterAug	0.176** (0.013)	Adopt*AfterJan	0.139** (0.010)
Friend_count	2.11E-05 (4.79E-06)	Friend_count	2.3E-05 (4.80E-06)	Friend_count	2.3E-005** (4.84E-06)
Follow_count	9.45E-08** (4.70E-09)	Follow_count	9.40E-08** (4.71E-09)	Follow_count	9.40E-08** (4.71E-09)
Statues_count	-8.49E-06** (3.83E-07)	Statues_count	-8.16E-06** (3.84E-07)	Statues_count	-8.16E-06** (3.84E-07)
Gender	0.028** (0.005)	Gender	0.030** (0.005)	Gender	0.030** (0.005)
Level	0.003** (3.81E-04)	Level	0.030** (3.82E-04)	Level	0.003** (3.82E-04)
Isvip	0.033** (0.006)	Isvip	0.036** (0.006)	Isvip	0.036** (0.006)
Regist_time	3.83E-06* (1.59E-06)	Regist_time	4.30E-06** (1.59E-06)	Regist_time	4.30E-06** (1.59E-06)

When we use each users' enrollment dates as breakpoints, our model reports significant positive difference-in-differences estimators for shifts in article supply (Table 3), article quality (Table 4a and 4b), article demand (Table 5), and microblog supply (Table 6), but the effect of monetization adoption has insignificant effect on microblog demand (Table 7). It indicates that the adoption of "tipping" function will significantly increase the verified users' motivation to write more articles with higher quality, and even more microblogs. At the meantime, the verified users will attract more article readers after adopting the tipping function. However, the demand of microblog is not significantly changed after participation in content monetization program. When we use August 2014, the starting of test period, as breakpoints, we also observed significant positive difference-in-differences estimators for shifts in article supply (Table 3), article quality (Table 4a and 4b), and article demand (Table 5), and microblog supply (Table 6), but insignificant estimator for shifts in microblog demand (Table 7). The estimation results when using January 2015 as breakpoints are consistent with that of August 2014 in direction but a bit larger in magnitude. We found that the difference in shifts of article supply, article quality, and article demand after policy changes between verified users and non-verified users (i.e. the coefficients of Verified*AfterAug and Verified*AfterJan) are both smaller than that after the enrollment dates (i.e. the coefficients of Verified*AfterEnroll). The shifts after open application are larger than that after the starting of the test period. It indicates that the announcement of content monetization program encourages non-verified users to make greater effort in article supply and quality control than the actual adoption effect of tipping function, even though "tipping" is only allowed for verified users during the test period. The greater efforts of non-verified users also win more article demand shifts after the policy changes than that after enrollment. This phenomenon is recognized as the spillover effect of content monetization policy. In terms of the microblog supply and demand, tipping button adopters have larger shifts in writing and consuming microblogs after enrollment and after policy changes compared with non-adopters. The shifts after open application become smaller than that during the test period.

In order to address the robustness of our empirical results based on DID model, we further conduct nearest neighbor matching estimators (Abadie and Imbens 2006) to compare the shifts of content amount and content quality generated by users from treatment groups with that from control group. Because we are unable to empirically propose an absolute exogenous instrument variables, we address the potential selection bias by matching adopters with non-adopters based on observables using a propensity score matching method. We use the pre-event and post-event observation for each user. We fist collapse each of our outcome variables Y_{it}, where Y ϵ {num_articles, num_characters, num_pictures, num_readings, num_microblogs}, into two month averages before and after two breakpoints: August 2014 and January 2015. We then generate new variables ΔY_I by taking the difference between the pre-event and post-event averages. We matched users based on individual attributes, such as gender, level, regist_time, etc., to control for any additional unobserved heterogeneity in content creation behavior. We use the matching algorithm by Abadie and Imbens (2006), which computes a distance score between a treated unit and all possible untreated neighbors based on the matching parameters, and then matches each treated unit with the closest three untreated units, with replacement. The exact procedure is implemented in the NNMATCH module for STATA. Table 8 shows the DID matching estimators across different treatment and control groups.

Table 8. DID matching estimator

outcome	Δnum_article		Δnum_chars		Δnum_pics		Δnum_reading		Δnum_micro	
Break points	Aug 2014	Jan 2015	Aug 2014	Jan 2015	Aug 2014	Jan 2015	Aug 2014	Jan 2015	Aug 2014	Jan 2015
Adopter vs Nonadopter	1.71** (0.19)	1.29** (0.20)	271** (51.97)	159** (21.34)	1.18** (0.14)	1.01** (0.19)	367** (91.05)	1892** (376)	3.20 (3.23)	5.52** (2.47)
Verified Adopter vs Nonadopter	2.86** (0.42)	2.08** (0.58)	293** (97.77)	248** (38.89)	1.98** (0.27)	1.20** (0.24)	754** (211)	4026** (973)	15.7** (5.47)	7.17 (6.10)
Common Adopter vs Nonadopter	-	0.84** (0.13)	-	93.9** (25.52)	-	0.41 (0.31)	-	532* (224)	-5.74 (4.16)	3.78** (1.01)
Verified vs Common Adopter	-	1.66** (0.55)	-	148** (68.78)	-	1.36** (0.40)	-	2269 (1256)	35.0** (8.861)	4.25 (12.42)
Verified vs Common Nonadopter	0.06* (0.03)	0	4.055 (39.76)	0	-0.029 (0.034)	0	-39.84 (33.44)	0	6.77** (3.19)	7.71 (6.35)

The adoption of content monetization in the test period is linked to 1.71 more articles supply, 271 more characters in average length, and 1.18 more pictures, while the amount changes reduce to 1.29, 159, and 1.01 respectively across open application period. As to the difference between verified adopters and non-adopters, we also observe larger increase in article supply (2.86 more articles) and article quality (293 more characters in average length and 1.98 more pictures) across August 2014 than the shifts across January 2015 (2.08 more articles, 248 more characters in average length, and 1.20 more pictures). It indicates that adopters after January 2015 are less motivated in article posting comparing with those verified adopters during test period.

From the article demand side, January 2015 witness a much larger increase in average number of readings than that happened in August 2015. But the changes of average reading number before and after January 2015 received by verified adopters and by common adopters do not have significant difference, which indicates that the platform construct a very healthy environment for common users to make fair competition with celebrities.

In terms of the change of microblog supply, the matching estimators indicate interesting result that the significant difference between verified and common adopters or non-adopters across the test period becomes insignificant during the open application period. In addition, the changes of microblog supply by verified adopters across test period is significantly 1.57 higher than that by verified non-adopters, but this figure also becomes insignificant across open application period. On the contrary, the insignificant difference between common adopters and common non-adopters across test period becomes significant (3.78 with p-value 0.00) across open application period. It implies that the policy change in January 2015 (allowing all users to apply for "tipping" function) demotivate the verified users' supply of microblogs but trigger common users to post more microblogs.

Discussion

According to the empirical results, content monetization mechanism exhibit a very deterministic role to increase both content supply and content demand in social media platform. Our study has three notable findings. First, the announcement of content monetization program as well as the actual adoption of tipping function significantly motivates weibo users, especially verified users, to participate in high quality content generation. At the initial stage, verified users make less effort in content supply and quality control compared with non-verified users (i.e. significantly negative coefficients of "Verified"). After the introduction of content monetization mechanism, we observe significantly larger increase in content supply and content quality on verified users than that on non-verified users. It indicates that the content monetization mechanism successfully encourages verified users to contribute more high-quality content. Along with the growth of content supply and content quality, the demand of high-quality content also increases significantly due to the introduction of content monetization mechanism.

Second, we found the impact of content monetization program may take effect before weibo users' actual adoption behavior. To be specific, many weibo users may start generating high-quality articles in preparation for enrolling in content monetization program right after the program's announcement, even though no monetary incentives can be obtained by non-verified users during the testing period. Thus, we observe smaller differences in shift of content supply and content quality between verified users and non-verified users after policy announcement than that after "tipping" enrollment. Furthermore, the constrained application of content monetization during testing period may generate spillover effects on ordinary weibo users' content supply efforts, so the differences in shift of content supply and content quality between verified users and non-verified users after the starting of test period (August 2014) is even smaller than that after open application (January 2015). On the other hand, such policy changes from restricted authorization to open application may depress verified users to some extent. The propensity score matching estimators show that adopters after January 2015 are less motivated in article posting comparing with those verified adopters during test period.

Third, in addition to article supply and demand, content monetization mechanism also positively affect the supply and demand of microblogs, which is regarded as a complementary product of articles in social media. The adopters of tipping function will also make additional effort on microblog posting, and in return attract more attention from other users in social media. We further explore the variation across verified adopters, verified non-adopters, non-verified adopters, and non-verified non-adopters, and found that the policy change in January 2015 (allowing all users to apply for "tipping" function) demotivate the verified users' supply of microblogs but trigger common users to post more microblogs. Therefore, content monetization mechanism not only brings economic incentives to professional content generation, but also drives the growth of casual content generation in social media.

Conclusion

In this paper, we devoted to understanding the impact of content monetization program on the supply and demand of both professional and casual content in social media. Results indicate that content monetization mechanism successfully motivates high-quality content contribution in social media, thus attract increasing content consumption. Furthermore, the economic incentives caused by content monetization mechanism even have a stronger effect on ordinary weibo users than on the verified users who have already been the experts, celebrities or other public figures in the society. The monetization mechanism builds up a healthy competition market in which start-up content creators are able to survive and earn profit even in markets that are dominated by famous celebrities. Overall, the content monetization mechanism in social media actives the whole market from both demand and supply sides.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (Nos. 91546107) and Zhejiang Natural Science Foundation (Nos. LR16G020001). The authors are grateful to the editor and reviewers for their invaluable and insightful comments that have greatly helped to improve this work.

References

Abadie, A., and Imbens, G. 2006. Large sample properties of matching estimators for average treatment effects. *Econometrica* (74:1), pp. 235–267.

Albors, J., Ramos, J. C., and Hervas, J. L. 2008. New learning network paradigms: Communities of objectives, crowdsourcing, wikis and open source. *International Journal of Information Management* (28:3), pp. 194-202.

Atanasov, V. A., and Black, B. S. 2014. Shock-based causal inference in corporate finance research. *ECGI-Finance Working Paper*, pp. 11-08.

Bateman, P. J., Gray P. H., and Butler, B. S. 2011. The impact of community commitment on participation in online communities. *Inform Systems Research* (22:4), pp. 841–854.

Berry, S., Levinsohn, J., and Pakes, A. 1995. Automobile prices in market equilibrium. *Econometrica: Journal of the Econometric Society*, pp. 841-890.

Chen, Y., Harper, F. M., Konstan, J., and Li, S. X. 2010. Social comparisons and contributions to online communities: A field experiment on MovieLens. *American Economic Review* (100:4), pp.1358–1398.

Chevalier, J. A., and Mayzlin, D. 2006. The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research* (43:3), pp. 345-354.

Dellarocas, C., Awad, N., and Zhang, X. 2004. Exploring the value of online reviews to organizations: Implications for revenue forecasting and planning. *ICIS 2004 Proceedings*, pp. 30.

Fader, P. S., and Winer, R. S. 2012. Introduction to the special issue on the emergence and impact of user-generated content. *Marketing Science* (31:3), pp. 369-371.

Faw, L. 2012. "Is Blogging Really a Way for Women to Earn a Living?," *Forbes*, April 25.

Gangi PMD, Wasko M, Hooker R. 2010. Getting customers' ideas to work for you: Learning from Dell how to succeed with online user innovation communities. *MIS Quarterly Executive* (9:4), pp. 163–178.

Gao, G., McCullough, J. S., Agarwal, R., and Jha, A. K. 2010. Are doctors created equal? An investigation of online ratings by patients. *In Proceedings of the Workshop on Information Systems and Economics (WISE)*, pp. 1-6.

Ghose, A., and Han, S. P. 2014. Estimating demand for mobile applications in the new economy. *Management Science* (60:6), pp. 1470-1488.

Goes, P. B., Lin, M., and Au Yeung, C. M. 2014. "Popularity Effect" in User-Generated Content: Evidence from Online Product Reviews. *Information Systems Research* (25:2), pp. 222-238.

Goh, K. Y., Heng, C. S., and Lin, Z. 2013. Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content. *Information Systems Research* (24:1), pp. 88-107.

Haklay M. 2010. How good is volunteered geographical information? A comparative study of openstreetmap and ordnance survey data sets. *Environment Planning B: Planning and Design* (37:4), pp. 682–703.

Hand, E. 2010. People power. *Nature* (466:7307), pp. 685–687.

Iriberri, A., and Leroy, G. 2009. A life-cycle perspective on online community success. *ACM Computing Surveys (CSUR)* (41:2), pp. 11.

Jabr, W., and Zheng, Z. 2014. Know Yourself and Know Your Enemy: An Analysis of Firm Recommendations and Consumer Reviews in a Competitive Environment. *MIS Quarterly* (38:3), pp. 635-654.

Jeppesen, L. B., and Frederiksen, L. 2006. Why do users contribute to firm-hosted user communities? The case of computer-controlled music instruments. *Organization Science* (17:1), pp. 45-63.

Lerner, J., and Tirole, J. 2002. Some simple economics of open source. *The Journal of Industrial Economics* (50:2), pp. 197-234.

Liu, Y. 2006. Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing* (70:3), pp. 74-89.

Lukyanenko, R., Parsons, J., and Wiersma, Y. F. 2014. The IQ of the crowd: understanding and improving information quality in structured user-generated content. *Information Systems Research* (25:4), pp. 669-689.

Majchrzak, A., and More, P. 2011. Emergency! Web 2.0 to the rescue! *Communication of the ACM* (54:4), pp. 125–132.

Mallapragada, G., Grewal, R., and Lilien, G. 2012. User-generated open source products: Founder's social capital and time to product release. *Marketing Science* (31:3), pp. 474-492.

Mishne G, and Glance N 2006 Predicting movie sales blogger sentiment. Proc. AAAI-CAAW-06, Spring Sympos. *Computational Approaches to Analyzing Weblogs (AAAI Press, Menlo Park, CA)*, pp. 155–158.

Moe, W. W., and Schweidel, D. A. 2012. Online product opinions: Incidence, evaluation, and evolution. *Marketing Science* (31:3), pp. 372-386.

Moon, J. Y., and Sproull, L. S. 2008. The role of feedback in managing the Internet-based volunteer work force. *Information Systems Research* (19:4), pp. 494-515.

Shen, W., Hu, Y. J., and Rees, J. 2015. Competing for attention: An empirical study of online reviewers' strategic behaviors. *MIS Quarterly* (39:3), pp. 683-696.

Shriver, S. K., Nair, H. S., and Hofstetter, R. 2013. Social ties and user-generated content: Evidence from an online social network. *Management Science* (59:6), pp. 1425-1443.

Singh, P. V., Sahoo, N., and Mukhopadhyay, T. 2014. How to Attract and Retain Readers in Enterprise Blogging?. *Information Systems Research* (25:1), pp. 35-52.

Susarla, A., Oh, J. H., and Tan, Y. 2012. Social networks and the diffusion of user-generated content: Evidence from YouTube. *Information Systems Research* (23:1), pp. 23-41.

Tirunillai, S., and Tellis, G. J. 2012. Does chatter really matter? Dynamics of user-generated content and stock performance. *Marketing Science*, (31:2), pp. 198-215.

Trusov M., Bodapati A. V., Bucklin R. E. 2010 Determining influential users in Internet social networks. *Journal of Marketing Research* (47:4), pp. 643–658.

Wattal, S., Schuff, D., Mandviwalla, M., and Williams, C. B. 2010. Web 2.0 and politics: the 2008 US presidential election and an e-politics research agenda. *MIS Quarterly*, pp. 669-688.

Zeng, X., and Wei, L. 2013. Social ties and user content generation: Evidence from Flickr. *Information Systems Research* (24:1), pp. 71-87.

Zhang, X., and Zhu, F. 2011. Group size and incentives to contribute: A natural experiment at Chinese Wikipedia. *The American economic review* (101:4), pp. 1601-1615.

Zwass V. 2010. Co-creation: Toward a taxonomy and an integrated research perspective. *International Journal of Electronic Commerce* (15:1), pp. 11–48.